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Using cumulative potential recharge for selection of GCM projections to force regional groundwater models: A Nebraska Sand Hills example

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A B S T R A C T

Groundwater recharge (GR) controls vegetation, geomorphology, groundwater, wetlands and surface flow, and ultimately, the ecology and economics of semi-arid regions. Therefore, it is critical to assess hydroclimate model scenarios and the uncertainty in future GR to force regional groundwater models. We use basic statistics of downscaled Global Circulation Model (GCM)-projected cumulative potential GR (GR_p) for selecting representative projections. Cumulative GR_p is the net recharge (difference between precipitation (P) and evapotranspiration (ET) rates) over the projection period. The approach is illustrated with an example in the Nebraska Sand Hills (NSH), the largest dune region in the Western Hemisphere, where sandy soils are not conducive to overland flow.

Changes in decadal-average GR_p at 1/8° (~12-km) scale were estimated from spatially downscaled, bias-corrected temperature and P output from 16 commonly used GCMs for years 2010 to 2099. These changes accounted for three greenhouse gas emissions scenarios, and projections were subsequently used as input to the Variable Infiltration Capacity (VIC) land surface hydrology model. For each of the 48 GCM/VIC hydroclimate projections, cumulative GR_p was calculated and averaged over the study area. Three projections (those with cumulative average GR_p nearest the median and ±1 standard deviation) were selected as representing Median, Wet and Dry conditions. These projections allow for rapid screening of the sensitivity of regional groundwater models, using readily available downscaled GCM-projected climate changes, thereby optimizing modeling efforts. Future GR_p was calculated for the NSH using the selected GR projections by adjusting the 2000–2009 baseline GR_p estimates at 1-km scale. The latter was inferred from a previously calibrated groundwater model, with ET based on remote sensing (MODIS) temperature data, and matching regional baseflows.

In the NSH by 2099, the Median projection indicates an increase in GR_p of 3 mm/yr (+5%) relative to the 2000–2009 baseline of 52.6 mm/yr. The Wet projection has an average increase of 22 mm/yr (+42%), and the Dry projection shows an average decrease of 15 mm/yr (−29%), relative to the baseline. Effects of projection period duration and time-step averaging on selection of GR projections with this approach are discussed. The new detailed GR_p projections clarify varying trends of past large-scale analyses of the Northern High Plains region and indicate the possibility for substantial future changes in the NSH hydrologic system. This approach can be extended to other arid-to-humid regions with available GCM hydroclimate projections.

1. Introduction

Groundwater modeling of land use and climate change impacts on groundwater recharge (GR), discharge, and aquifer levels has become an increasingly urgent topic in groundwater science (Candela et al., 2009; Doble and Crosbie, 2017; Goderniaux et al., 2011; Green et al., 2011; Hanson et al., 2014; Maxwell and Kollet, 2008; Meixner et al., 2016; Rosenberg et al., 1999; Scibek and Allen, 2006; Taylor et al., 2013; Wanders and Van Lanen, 2015; Woldeamlak et al., 2007; York et al., 2002). These changes commonly pose major threats to surface water features, such as groundwater-fed lakes and wetlands, as groundwater systems respond to changing GR (Green et al., 2011), sometimes with disastrous ecological and economic consequences (e.g., Tao et al., 2015). This issue is especially important in arid and semi-arid environments where groundwater discharge often dominates the water balance of streams and lakes and supports their existence. Changing groundwater levels and coverage of lakes and wetlands can

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affect groundwater-dependent ecosystems (Klove et al., 2014) and agriculture where plants are sub-irrigated by groundwater, such as in the Nebraska Sand Hills (NSH) (Harvey et al., 2007), an important GR area of the High Plains Aquifer (Scanlon et al., 2012). Drying lakebeds in these systems act as preferential dust source areas, contributing disproportionately to global dust emissions (Tegen et al., 2002; Ginoux et al., 2012). These issues are at the center of an area of intensive research integrating groundwater modeling, remote sensing, and field observations.

For modeling purposes, research institutions and management agencies rely on already available studies of GR derived from of Global Circulation Model (GCM) projections. In such cases, development of GR projections is just a stage of a larger project that must consider other drivers of change, such as land use and resource demands (Snover et al., 2013; Vano et al., 2015). Thus, sets of various projections are constrained by the capacity to assess and incorporate available climate change scenarios into the planning, or modeling, process. For example, Meixner et al. (2016) generalized implications of projected climate change for GR in the western United States and found that modeling studies of projected climate-change effects had been carried out for about half of the reviewed aquifers. In contrast to that, studies with emphasis on GR commonly strive to incorporate all possible GCM projections. Table 1 presents a few representative examples for illustration purposes.

Studies of Rosenberg et al. (1999), Scibek and Allen (2006), Toews and Allen (2009), Allen et al. (2010), provide examples of groundwater models of different scales with different number of GR projections used, from a small number of GCMs. Selection of GCMs and projections used *ad hoc* considerations, as also was shown by Meixner et al. (2016). In contrast to that, studies by Crosbie et al. (2010, 2011, 2013) and Tillman et al. (2017) were dedicated entirely to GR mapping, following numerous studies based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) projections. In analyses, Crosbie et al. (2013) used 49 projections, and Tillman et al. (2016) explored 97 projections. In both cases, increasing the projections subsets and inference of statistical properties was recommended for future GR studies.

Processing of the ever-growing number of GCMs and GHG scenarios may produce additional information and characteristics of the entire set of projections. However, use of each projection as an input for groundwater modeling and analysis of the resulting output dataset may not be an optimal strategy. Rather, selected representative projections should be used for groundwater modeling with moderate size datasets of GR projections. Then, the characterization of the sensitivity of the regional groundwater systems to GR changes, and analyses of the modeling uncertainty, becomes more efficient. Despite this need to rationalize the number of climate scenarios in impact-modeling assessments, there is a limited focus toward methods of effectively using GCM-derived information (e.g., Vano et al., 2015). Starting from pioneering work by Rosenberg et al. (1999), groundwater recharge and groundwater modeling studies vary by the numbers of GCM projections used

Table 1
Using GCMs for groundwater recharge projections.[a]

Reference	Region, area[b]	Methods for GR inference	# GCMs / #projections	Period[c]	Rationale for selecting # of projections
Rosenberg et al. (1999)[d]	Missouri and Arkansas-White Red basins, High Plains Aquifer, USA, area estimate is in excess of 400,000 km^2	SWAT	4 / 30	2000–2100	Ad-hoc selection (ibid, p. 681)
Scibek and Allen (2006)[d]	Grand Forks aquifer, British Columbia, Canada, and N. Dakota, USA, area estimate in excess of 12,000 km^2	MODFLOW	1 / 1	2010–2039 2040–2069	Ad-hoc selection (ibid, p. 175)
Toews and Allen (2009)[d]	Oliver Region, British Columbia, Canada, area estimate in excess of hundreds of km^2	HELP 3.80D	3 / 3	2040–2100	Ad-hoc selection (ibid, pp. 268–269), A1-A2 scenarios
Allen et al. (2010)	Abbotsford-Sumas aquifer, British Columbia, Canada, and Washington, USA, 161 km^2	HELP LARS-WG	4 / 4	2010–2080	Ad-hoc selection (ibid, p. 5 or W00F03)
Ng et al. (2010)	Southern High Plains segment, New Mexico and Texas, USA, 75,500 km^2	SWAP 3.0.3, LARS-WG	5 / 5	2010–2085	Ad-hoc selection (ibid, p. 8), seeking representative “driest”, “all dry”, “wet”, “intense”, and “seasonal” rainfall
Crosbie et al. (2010)	Three locations in Murray-Darling Basin, Australia, 1,060,000 km^2	WAVES	15 / 45	2030	Ad-hoc selection (ibid, p. 1641). One of results: fit of the Person III Type distribution to GR data, specific for 2030
Crosbie et al. (2011)	15 locations in Murray-Darling basin, Australia, 1,060,000 km^2	WAVES	5 / 5	2046–2065	Ad hoc selection, emphasis on uncertainty of downscaling (ibid, p. 1). Increasing # of projections to use probabilistic framework is hypothesized (ibid, p. 4).
Crosbie et al. (2013)	17 locations over High Plains Aquifer, USA, 450,000 km^2	WAVES	16 / 49	2013–2050	Maximized # of GCMs and projections is used. Three projections (median, wet, and dry) are selected based on 2050 GR data. Pearson III Type distribution (ibid, p. 6) was used.
Tillman et al. (2017)	Upper Colorado River Basin (Wyoming, Colorado, Utah, New Mexico, and Arizona), USA, 280,000 km^2	SWB	97 / 31	2016–2099	Maximized # of GCMs and projections is used. Just median GR from 2100 data was recommended in Conclusions (ibid, p. 6). Uncertainty bounds are defined by boxplots.
This article	Sand Hills, Nebraska, USA, 40,000 km^2	VIC	48 / 16	2010–2049 2010–2099	Maximized # of projections is used. Median, wet, and dry GR projections selected, specific to the projection period: 2010–2049 or 2010–2099. Uncertainty bounds (wet and dry scenarios), defined by SD, which is related to the projection period. Pearson III Type distribution does not apply.

[a] List of studies of GCM applications is not exhaustive by any means; it illustrates evolution of ideas to constraint the use of GCM information.
[b] Area is given approximately, when not reported directly.
[c] Calibration periods are omitted.
[d] GR projections are explicitly used for modeling.

(Table 1). In this aspect, the study of Allen et al. (2010) exemplifies the inherent problem of a growing number of both GCM models and greenhouse gas (GHG) emissions scenarios. Conducting regional studies required modeling the GR and groundwater flow, and they considered only four GCMs and two GHG scenarios (i.e., eight climate change projections) for an aquifer on the border of Canada and the US (area of 161 km^2). Alternatively, Tillman et al. (2016) studied GR for the upper Colorado River basin (293,721 km^2) using 97 GCM projections, but without groundwater modeling. These approaches to GR estimation differ greatly in detail based on the amount of available modern climate data used and GCM projections. Therefore, it is desirable to have a simple method for summarizing the wealth of possible GR projections and their uncertainty before undertaking more in-depth studies, such as forcing diagnostic regional groundwater flow models.

We use a simple approach to the task of identifying and selecting three representative GR scenarios for groundwater modeling, while capturing the variability inherent in the set of individual projections based on GCMs and GHG scenarios. Unlike Ng et al. (2010) or Crosbie et al. (2013), this approach is based on analyses of gridded cumulative potential GR and consists of the following steps:

(1) Selection of the duration of the projection period;
(2) Identification of GCMs, GHG emissions scenarios, and land surface hydrology models;
(3) Assessment of future changes in the net potential groundwater recharge (GR_p)—as the difference between GCM-projected mean precipitation (P) and (coupled) land surface hydrology model-simulated actual evapotranspiration (ET);
(4) Compilation of GR_p datasets and calculation of statistics of cumulative (over the projection period) spatially-averaged GR_p for all GCMs and GHG emissions scenarios; and
(5) Identification of representative Median, Wet, and Dry GR projections.

These steps result in the necessary GR inputs for regional groundwater modeling.

We will illustrate the idea with a focus on the Nebraska Sand Hills (NSH), a 40,000-km^2 portion of the Northern High Plains Aquifer region with total area of ~450,000 km^2. Rosenberg et al. (1999, Table III) estimated reductions of GR for the entire Missouri River Basin of about the same total area as the High Plains Aquifer. Reductions of GR in the Northern High Plains Aquifer region were predicted to range between 10% and 17%, based on one of three selected GCMs and three GHG emissions scenarios. Crosbie et al. (2013) presented GR study for entire High Plains Aquifer region using 16 GCMs and three GHG scenarios, and found a substantial qualitative difference in GR dynamics between the Northern and Southern High Plains Aquifer regions in 2050: the most southern parts may experience a future decrease in GR, while the northern parts may even exhibit a modest increase. Meixner et al. (2016) found similar latitudinal trends in analyses of future GR in the western United States. We will address variance in predicted trends using only limited number of projections.

The primary objective of our study is to demonstrate an approach to the assessment of the GCM-projected net GR_p changes in the NSH region, including the range and most likely possible projections for the 21st century. Furthermore, this approach specifically evaluates temporal variability of future GR projections, and how this GCM selection approach is influenced by choice of projection period duration. This approach can be used for diagnostic analyses of climate and land use-related changes for regional groundwater modeling in many areas of the world.

2. Study area

In the semi-arid dune environment of the Nebraska Sand Hills (NSH)—the largest continuous dune region in the Western Hemisphere (Ahlbrandt and Fryberger, 1980)—many streams and several thousand natural groundwater-fed lakes and wetlands exist in hydraulic connection with the Northern High Plains Aquifer (Fig. 1). They are supported by the highest GR rates of the entire High Plains Aquifer region (Crosbie et al., 2013; Scanlon et al., 2012), averaging more than 70 mm/yr, and exceeding 270 mm/yr in some areas (Szilagyi et al., 2011). The absence of overland flow due to the high infiltration capacity of the sands (Bleed and Flowerday, 1998) suggests that groundwater, derived from local precipitation, is the primary source of water to lakes and streams (Bleed and Flowerday, 1998). Current water resources are plentiful in the region, providing relatively steady water inputs to the downstream Platte River basin and drinking water for cities with total population of about one million. Irrigation in the NSH study area (Fig. 1) is limited due to the sandy soils and variable topography, and land use change is expected to be negligible, so these effects are unlikely to obscure the effects of future climate change.

However, little is known about hydrological vulnerability of the NSH due to 21st century climate change (Bathke et al., 2014). What is known from tree rings, archeological remains, lake sediment, and geomorphic data, is that alternating humid and dry periods have been common over the Holocene (Miao et al., 2007), with numerous documented occasions of extensive and extended drought over the last 10,000 years in the Great Plains (Woodhouse and Overpeck, 1998). Moreover, droughts of greater duration and severity than observed during the instrumental record have occurred as recently as 700 years ago, and were accompanied by dune migration (Loope et al., 1995; Miao et al., 2007).

3. Methods

3.1. Selecting set of future climate models for groundwater recharge estimation

The steps taken in the process of generating GR data for regional groundwater modeling at a 1-km resolution in the Sand Hills of Nebraska are outlined in Fig. 2 in eight steps (diagram blocks). The set of GCMs and scenarios contains uncertainties of two kinds: 1) differences in the simulated processes and parameterization of GCMs; and 2) global and regional climate dynamics, driven by differences in future GHG emissions.

Here, we made use of CMIP3 model results (Meehl et al., 2007), rather than CMIP5, to enable comparisons to previous work and because CMIP5 climate projections change little from CMIP3 projections over the central Great Plains (Brekke et al., 2013). An ensemble of bias-correction spatial disaggregation (BCSD) climate and hydrology projections, downscaled from 16 GCMs and 3 GHG emissions scenarios, was obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive (http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/). The GCM model projections used in this study were forced by three GHG emissions scenarios (A2, A1B, and B1) after IPCC SRES (Nakicenovic et al., 2000), covering a wide range of demographic, economic and technological driving forces leading to differences in GHG emissions and global surface temperatures. These downscaled projections were then utilized to determine future GR projections for the 21st century.

Monthly gridded values of P and ET for the entire 21st century, spanning the Missouri River basin with a spatial resolution of 1/8° (~12-km), were downloaded from the archive using a single run of

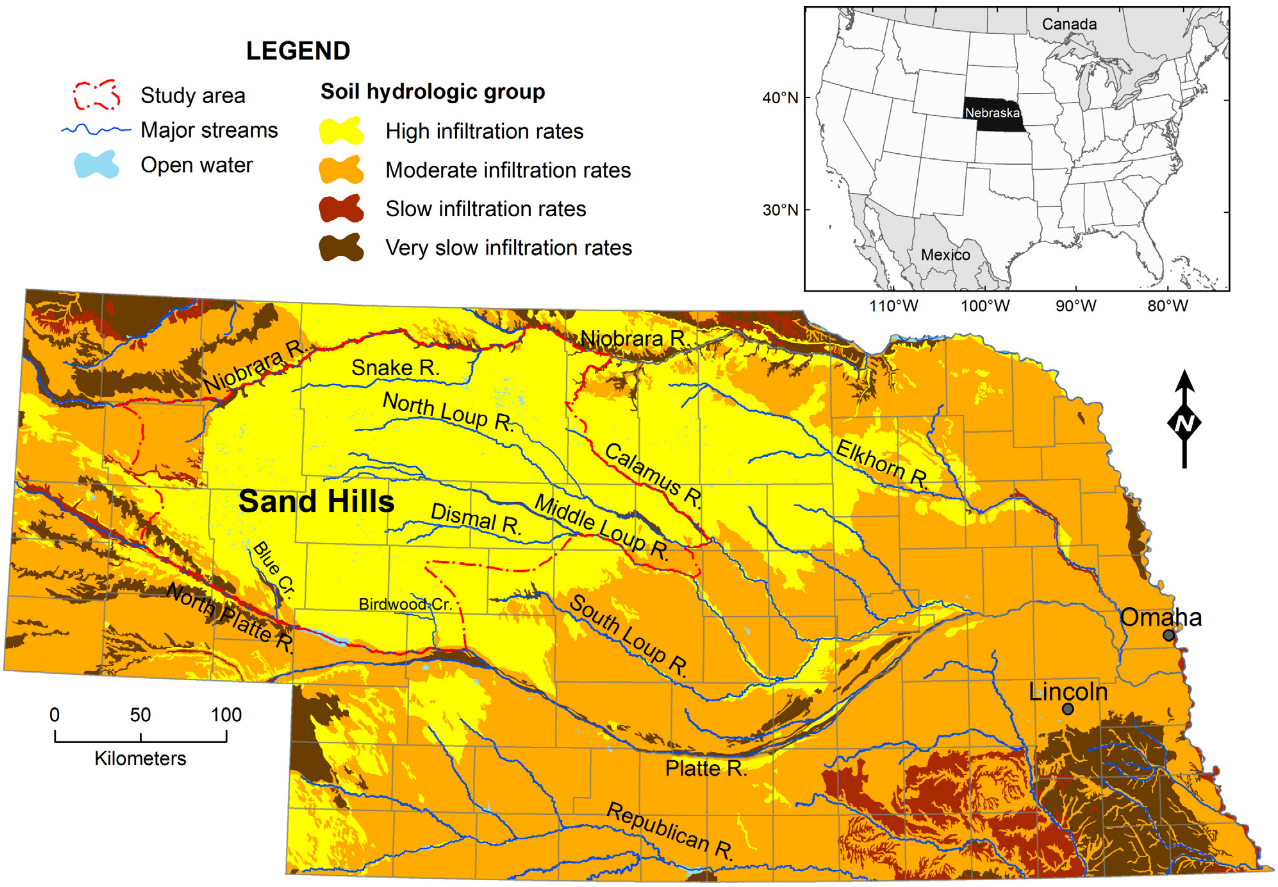

Fig. 1. Study area (outlined in red covering the majority of the Sand Hills region) and major statewide soil series of Nebraska with relative infiltration rates (data from the U.S. Department of Agriculture, Natural Resources Conservation Service, State Soil Geographic (STATSGO Data Base). Grey lines are county boundaries; blue lines are major rivers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

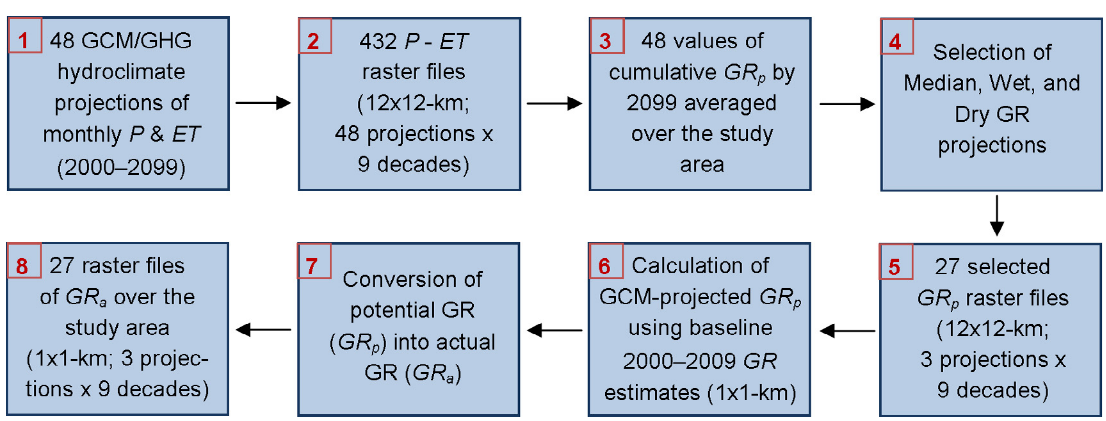

Fig. 2. Workflow for selection of Median, Wet, and Dry GR projections using 12 × 12-km resolution cumulative GR_p as $P - ET$, with ET from the land surface hydrology model, VIC, and conversion to a 1-km resolution grid of baseline 2000–2009 GR estimates.

each (16) GCM and each (3) GHG emissions scenario, a total of 48 combinations (Fig. 2, block 1; USBR, 2011). The downloaded hydrology variable ET was produced using the Variable Infiltration Capacity (VIC) macroscale land surface hydrology model applying the Penman-Monteith equation and allowing for deep drainage (Liang et al., 1994; Niraula et al., 2017).

The archive of CMIP3 hydroclimate model projections provided the necessary P and ET data to generate future GR_p changes from 2010 through the end of the 21st century as follows. For each of the 48 combinations of GCMs and GHG emissions scenarios, GR_p was calculated using a water balance approach as the mean decadal difference between P and ET, considering that overland flow is minimal due to high infiltration rates in the NSH (Bleed and Flowerday, 1998). Averages of GR_p, at the downscaled GCM grid scale (12-km), over each 21st century decade (2000–2009, 2010–2019, …, and 2090–2099) were calculated and clipped using ArcGIS to cover only the study area (Fig. 2, block 2). The same (P – ET) water balance approach, relying on remote sensing

measurements, has been implemented successfully in the NSH region (Szilagyi et al., 2011) and the entire state of Nebraska at 1-km resolution (Szilagyi and Jozsa, 2013), and elsewhere (e.g., Brunner et al., 2007; Crosbie et al., 2014), to estimate spatially distributed GR rates, and for inputs to groundwater flow models.

The GR_p from different GCMs may vary during the projection period, complicating the comparison of various GR projections; for example, a "wet" projection may become "dry" for a certain period, or *vice versa*. For instance, the A1B scenario projects the largest increase in global temperatures between about 2000–2060, while A2 exceeds A1B in surface warming after 2060 (up to 3.6 °C in 2100, relative to 2000). Meanwhile, the B1 scenario shows the smallest increase in surface temperature. Similarly, changes in *P* in the future are projected by the GCMs, but in the central U.S., and in Nebraska itself, there is little agreement of the overall direction of changes in the long-term average (Christensen et al., 2007; IPCC, 2014), causing the relatively high uncertainty in projections of future GR in this region. However, in the last thirty years of the 21st century (2071–2099) increases in *P* of 0–20% are expected over winter and spring months, with decreases of 0–20% over summer months, and insignificant trends in the fall months (Karl et al., 2009; Walsh et al., 2014).

Greenhouse gas emissions scenarios, followed by differences among GCMs, are the dominant sources of uncertainty in future GR estimation (Crosbie et al., 2011, 2013) and the ensemble of 48 climate projections used in this study represent a wide range of these main sources of uncertainty. Other lesser sources of uncertainty, such as from the choice of downscaling method or land surface hydrological model selected and its parameterization (VIC model used here), were not considered in this study. Niraula et al. (2017) provide a comparison of three different land surface hydrology models applied across the western U.S., concluding that VIC and Noah are the best suited tools for potential recharge estimation. From a water management perspective, or for protection of aquatic habitat, it is likely best to have a possible range of outcomes and plan accordingly, rather than plan for the average likelihood alone (Allen et al., 2010). To represent the range of possibilities, there is a need to select at least one dry and one wet projection. Here we choose three projections, of the 48 analyzed, by way of analysis of cumulative potential GR. The following section describes the basis on which the GCM projections were selected.

3.2. Evaluating GCM projections by cumulative potential groundwater recharge, GR_p

Diffuse groundwater recharge is the major driver, and often largest water budget component, of many groundwater systems. To compare all available GR projections, we calculated cumulative GR_p from each GCM projection averaged over the study area from the beginning to the end of the projection period (Fig. 2, block 3), resulting in the curves shown in Fig. 3. The descriptive statistics of the 48 cumulative spatially averaged GR_p were then used to select three GR projections—those closest to the median cumulative GR_p and ±1 standard deviation (SD) from the median, represent Median, Wet, and Dry conditions (Fig. 2, block 4). This process removes 405 raster files of decadal GR_p over a 90-year projection period, resulting in 27 GR projections (12 × 12-km raster files) remaining for use to force the groundwater model (Fig. 2, block 5).

As mentioned above, the duration of the projection period may play a significant role in selection of GR projections. To illustrate the role of the projection period duration, we compare 40-year and 90-year projections and show differences that could arise in the final selection of representative Median, Wet, and Dry GCM projections of GR changes.

3.3. Calculation of future potential groundwater recharge rates

Our approach to calculation of future GR_p rates is to superimpose decadal changes from the three selected GCMs/VIC (12 × 12-km) hydroclimate projections onto the modern conditions of 2000–2009 (baseline), accounting for variations of projected GR_p (Fig. 2, block 6). While of secondary concern with respect to the objectives of this article, this step was carried out to provide 1-km resolution future GR estimates for direct application to a transient groundwater model, and to discuss changes relative to an arguably more accurate baseline than could be provided by the bias-corrected, spatial disaggregation GCM/VIC hydroclimate projections. It is important to note that all GCM estimates of GR_p for 2000–2009 (at 12 × 12-km scale) have some bias with respect to the baseline estimate. Therefore, for transient groundwater modeling, this bias is corrected by adjusting baseline estimates (1 × 1-km) by the decadal changes obtained from GCMs (Fig. 2, block 7).

Baseline GR_p (2000–2009) estimates were derived from MODIS land surface temperature satellite measurements and other ancillary climate data (Szilagyi and Jozsa, 2013; Szilagyi et al., 2011) and were slightly adjusted during calibration of a previously developed steady-state MODFLOW-based groundwater model with 1-km horizontal grid cell resolution (Rossman, 2015; Rossman et al., in press). After calibration of the groundwater model to water levels and regional baseflow to streams, the spatially averaged baseline GR_p (from 2000 to 2009) equaled 52.6 mm/yr, ~15% greater than the MODIS-derived original GR_p estimate (46 mm/yr) of Szilagyi and Jozsa (2013) over the same time period and study area. In addition to having fine spatial resolution (1-km), baseline GR_p has complete coverage of the study area and both positive and negative net GR rates, regarded as requirements for regional groundwater flow modeling in shallow groundwater systems (Szilagyi and Jozsa, 2013).

4. Results and discussion

4.1. Median, Wet, and Dry projections

Averaged over the study area, net cumulative 2010–2099 potential groundwater recharge (GR_p) for the 48 GCM/VIC hydroclimate projections had a median of 4.970 m (55.2 mm/yr), a mean of 5.080 m (56.4 mm/yr), a standard deviation (SD) of 1.548 m (17.2 mm/yr), and a range of 6.884 m (76.5 mm/yr). Minimum cumulative 2010–2099 GR_p equaled 2.468 m (27.4 mm/yr) and the maximum equaled 9.351 m (103.9 mm/yr) (curves shown on Fig. 3). Fig. 4 depicts maps of the cumulative GR_p from 2010–2099 for the three selected GR projections. The spatial variability is due to the gradients in climate, topography, land cover/use, and, to a lesser degree, soils. The magnitude of the spatial variability, quantified by SD for each decade, remains roughly the same throughout the 21st century, with no apparent trend projected by the 48 GCM/VIC hydroclimate projections assessed (Fig. 5). The SD of the decadal GR_p rates varies in time between 19.2 mm/yr and 27.0 mm/yr (36.6% and 51.4% of the baseline GR_p rate, respectively).

Following the selection criteria described herein, by the end of the century (2090s) the selected Median GCM/VIC projection yields a spatially averaged increase in GR_p of 3 mm/yr (+5%), relative to the 2000–2009 baseline estimate of 52.6 mm/yr. The Wet projection yields an average increase of 22 mm/yr (+42%), and the Dry projection yields an average decrease of 15 mm/yr (−29%), relative to the baseline. These projected changes in GR_p are consistent with other large-scale analyses in the region (e.g., Meixner et al., 2016) and nearby in Colorado (Tillman et al., 2016), and indicate the

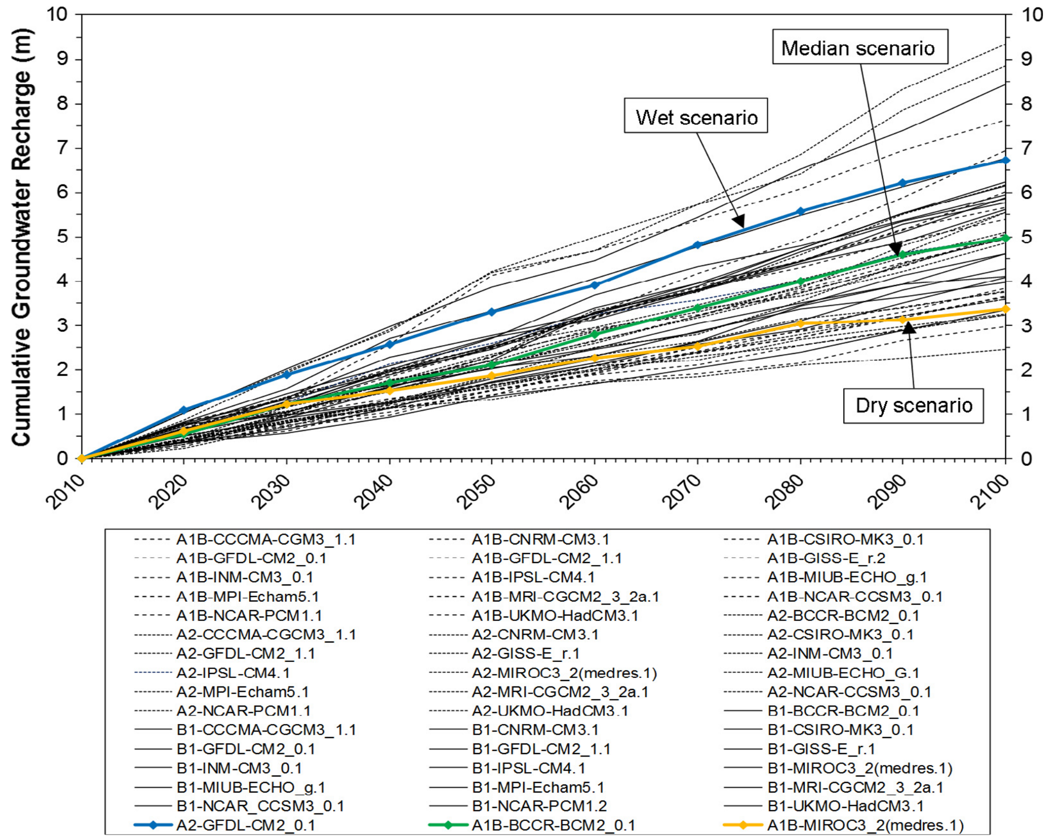

Fig. 3. Dynamics of cumulative GR projections from 2010 to 2099 based on mean decadal $P - ET$ of 16 GCMs under three GHG emissions scenarios. Lines styles indicate GHG emissions scenario (A2, A1B, and B1). Selected scenarios, based on the descriptive statistics of spatially averaged cumulative GR_p, are indicated by callouts (and color): Median (green), Wet (blue), and Dry (orange), corresponding to Fig. 2 (block 4). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

possibility for substantial future changes in the groundwater system and its connected surface-water features, with the tendency of the Median projection towards a slight increase in GR. For the NSH, such quantification has substantially higher resolution than previous studies (cf., Crosbie et al., 2013; Meixner et al., 2016), with direct implications for applications in transient regional groundwater flow modeling.

The 48 GCM/VIC hydroclimate model projections each have considerable variability from decade to decade (Fig. 5). The coefficient of variation (CV; SD divided by the mean) of decadal average GR_p from 2010 to 2099 varies from 0.43 to 0.66, and averages 0.55. For comparison, the average CV of the three selected GR projections selected are 0.55 (Median), 0.49 (Wet), 0.43 (Dry). Thereby, the selected GR projections capture most, but not all, of the full range of potential future GR variability displayed by all 48 GCM/VIC hydroclimate projections assessed. Interestingly, the Dry projection indicates generally wetter conditions over 2010–2030, and GR for the Median projection can exceed or almost equal the Wet projection GR (e.g., 2050–2060 and 2080–2090).

4.2. Temporal and spatial trends

The temporal changes in the three GR_p projections (Fig. 5) have similar magnitudes and range of uncertainty as those published for the Northern High Plains Aquifer region by Crosbie et al. (2013) and the upper Colorado Basin by Tillman et al. (2017). GR is projected to decrease in lower recharge areas in the Southern and Central High Plains Aquifer regions, while slightly increasing in the Northern High Plains Aquifer region. Results have a similar spatial trend as those that can be inferred from Rosenberg et al. (1999) who found smaller decreases of recharge in the entire Missouri River basin compared to the Arkansas River basin. However, Rosenberg et al. (1999) did not single out the NSH region specifically and lumped watershed areas of possible increase in Nebraska with areas of GR reduction in Kansas, thereby projecting slight overall decreases. In general, future GR reductions decrease northward, ultimately becoming an increase in Nebraska. These results are consistent with Cook et al. (2015), indicating moderate to severe decreases in GR rates and increases in drought indices, based on analysis of the Palmer Drought Index and soil moisture metrics. Interestingly, Tillman et al. (2017) found a similar trend of GR increase by 2099 at the same latitude in the upper Colorado Basin: decadal averages yielded increases by approximately 5% to 10%, based on 97 climate change projections. Meixner et al. (2016) drew similar conclusions for the Northern High Plains Aquifer region.

Changes in future GR rates may be positive or negative depending on changes in the intensity of rainfall (Allen et al., 2010; Toews and Allen, 2009), and on the fraction of precipitation falling as either rain or snow (Jyrkama and Sykes, 2007). A possible additional factor for the increases in future GR rates in the NSH region is that the soils are substantially more permeable than in surrounding regions. The finding here that a slight increase in GR is the most likely for the NSH, indicates that the GCMs, the statistical downscaling method used (USBR, 2011), and the land surface hydrology model (VIC), are capable of accurately simulating the processes that determine P and ET. However, there is potential for VIC to systematically underestimate current ET rates as the version implemented does not explicitly account for the many small lakes in the NSH (USBR, 2011), and because it does not account

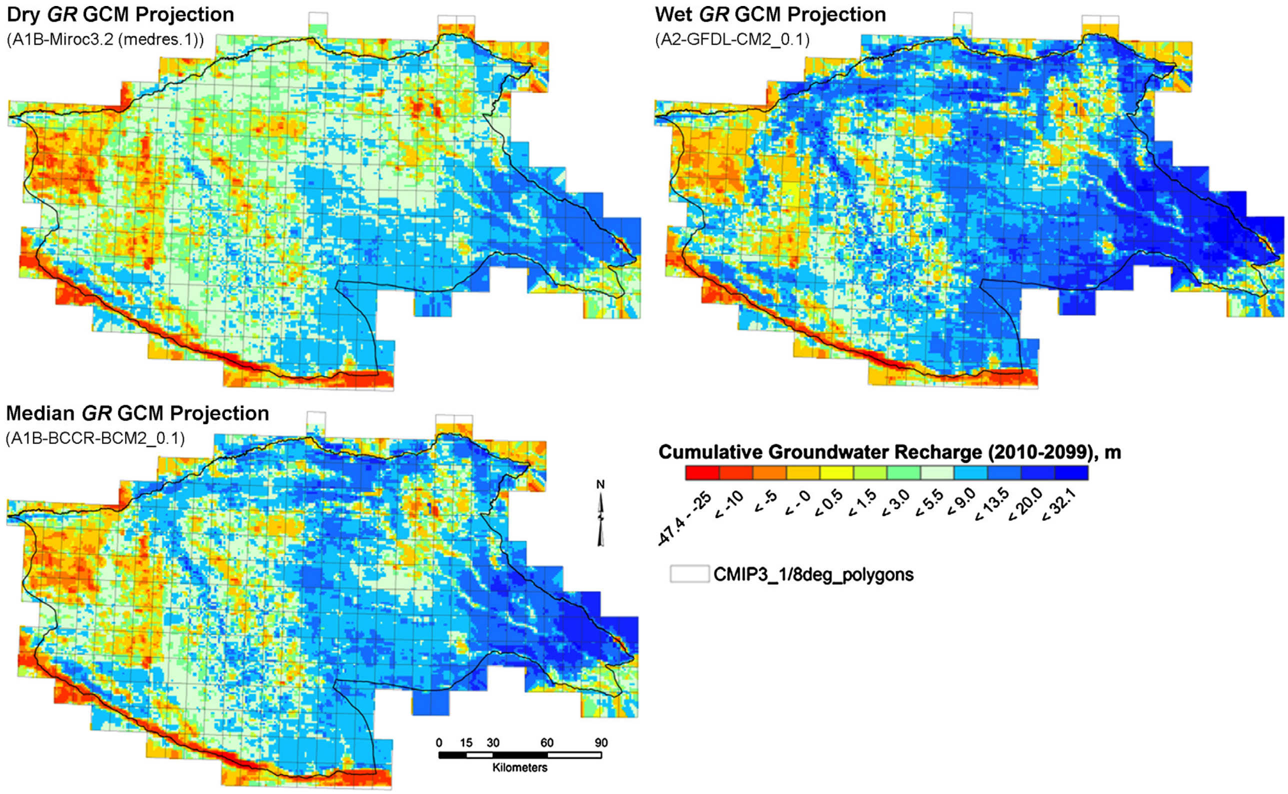

Fig. 4. Spatial variability of cumulative GR_p over the 90-year projection period (2010–2099) of the three selected GCM/VIC GR projections (Median, Wet, and Dry). Data shown have a pixel size of 1 km; the 1/8° (~12-km) grid of the downscaled GCM data is also shown. Color-coded classes are unequal in order to contrast areas of recharge and discharge while showing details in different parts of the scale. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

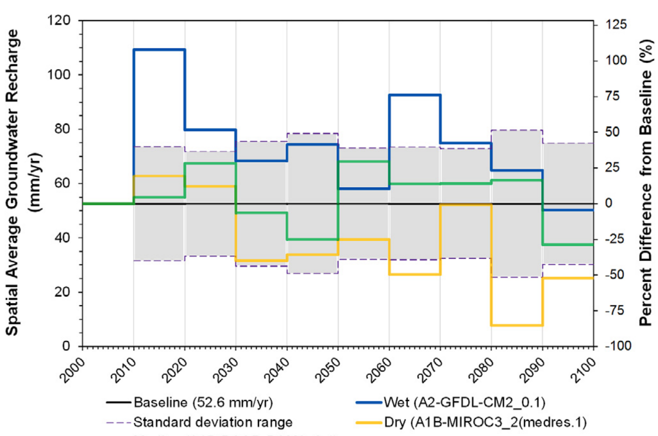

Fig. 5. Spatial average GR_p rates from the three selected Median, Wet, and Dry GR projections over the study area for 2010–2099 with a decadal time step, and their changes relative to the baseline from 2000–2009 (52.6 mm/yr). For evaluation of the uncertainty range in the selected GCMs, the standard deviation range (grey shading within purple dashed bounds) for all 48 GCM/VIC hydroclimate projections is plotted by decade. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for lateral groundwater flow at basin scales, thus affecting land-surface moisture states (Taylor et al., 2013).

4.3. Effects of projection period duration

The approach used here to find representative (Median, Wet and Dry) GR projections involves elements of subjectivity, especially for Wet and Dry projections, even when ranges for the NSH and upper Colorado (Tillman et al., 2016) are encouragingly similar in magnitude. Datasets of cumulative GR_p (whether 48 or 97 GCM scenarios) may not have a normal distribution. For example, Crosbie et al. (2010) proposed using Pearson Type III distribution fitted to a set of GR_p at the final date of the projection period. More importantly, it is apparent that the duration of projection period affects cumulative GR_p statistics and selection of Median, Wet, and Dry projections. To illustrate this point, we applied our approach for comparing such GR_p projections in the study area between period 2010–2049 and period 2010–2099 using histograms of cumulative GR_p at final years (Fig. 6; see also Table S1 of the Supplementary Material).

Comparison of these histograms shows that SD (spread in selection of representative projections) is higher for longer forecast periods; visual inspection also indicates that the use of lognormal or Pearson Type III distributions becomes more plausible. Clearly, representative Median, Wet and Dry projections are different for each projection period (Table 2 and Table S1 of the Supplementary Material).

There are other ways of summarizing statistics of projections, including quartiles and box plot diagrams. However, the reliance on SD in defining uncertainty bounds for representative projections is simple, provides plausible projections, and is a visual approach to preparing input data for groundwater models.

4.4. Time step in projections

The ultimate goal of this study is to apply representative projections in transient groundwater flow models. Here, time steps are defined by accuracy requirements of numerical method and data.

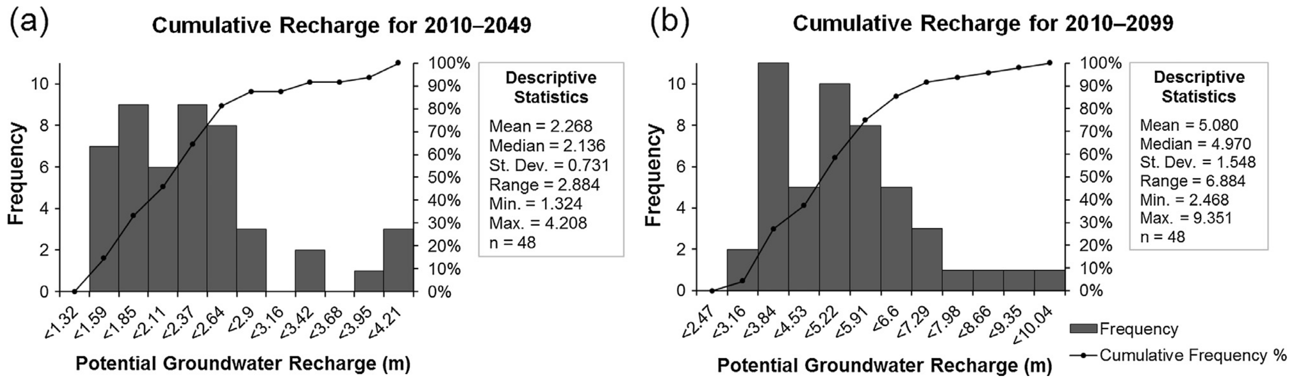

Fig. 6. Histograms of the spatial average cumulative GR_p for different projection period durations from 48 GCM/VIC hydroclimate projections: (a) 2010–2049 (40 years) and (b) 2010–2099 (90 years).

Table 2
Spatial average cumulative GR_p (m) over different projection periods.

GR_p Projection	Period 2010–2049		Period 2010–2099	
	GHG scenario/GCM	GR_p (m)	GHG scenario/GCM	GR_p (m)
Dry	B1 – miub_echo_g.1	1.387	A1B – bccr_bcm2_0.1	4.976
Median	B1 – ipsl_cm4.1	2.120	A1B – miroc3_2_medres.1	3.381
Wet	B1 – ncar_pcm1.2	2.765	A2 – Gfdl_cm2_0.1	6.723

In regional groundwater models, smaller time steps (daily to monthly) are rarely required or applied (Rossman and Zlotnik, 2013), as time steps or stress periods are typically on the time scale of years and longer. However, there is also a hydrological constraint—time steps must be at least as long as it takes for infiltrating water from precipitation to traverse the vadose zone. Potential groundwater recharge (GR_p) will become actual groundwater recharge (GR_a) after a certain vadose zone lag time—the time required for moisture changes to traverse the vadose zone before reaching the water table (Fig. 2, block 7; cf., Rossman et al., 2014). Although, this constraint does not exist for models where vadose zone soil moisture flow is calculated using physically based numerical modeling codes, for example those solving Richards' equation in three dimensions (e.g., Parflow, HydroGeoSphere, see Maxwell and Kollet, 2008). In more traditional groundwater modeling applications (e.g., MODFLOW), the vadose zone lag time between GR_p and GR_a must be introduced. Rossman et al. (2014) show that in 90% of the NSH, this lag time is less than 10 years under the baseline 2000–2009 climate with an analytical solution requiring only vadose zone thickness and long-term average GR_p. In modeling of the NSH and other cases of thick vadose zones, this constraint affected the selection of the decadal GR_p temporal averaging that was used. With such a time step, GR_a effectively equals GR_p in the NSH (Fig. 2, block 8). In general, large vadose zone thickness and low-permeability soils/rocks in the vadose zone may require assessment of lag time as it may be longer than 10 years in other basins, or under different climatic conditions (e.g., Cook et al., 2003; Rossman et al., 2014). This would be true of large portions of the Central and Southern High Plains Aquifer, and other areas, generally in semi-arid or arid climates.

4.5. Applying other projection measures

More complex, time-dependent measures of projections, such as the Aridity Index or Palmer Drought Severity Index, could be used for comparison of various projections (Dai and Zhao, 2016). However, evaluation of cumulative GR_p is especially attractive for groundwater modeling since it can be directly applied as input to transient models, and the variable is considered in conceptual assessments of regional water budgets of groundwater systems. Furthermore, in areas with lower infiltration capacity and higher overland flows, the approach used here is still useful, only the land surface hydrology model output of deep drainage should be used in the groundwater model, instead of $P - ET$. In regions where this is the case, the vadose zone thickness ought to be considered, as well as the time shift between potential GR (GR_p) and actual GR (GR_a) at the water table (e.g., Cook et al., 2003, Rossman et al., 2014).

5. Summary and conclusions

Regional groundwater modeling is a standard tool for estimating the effects of future land use and climate changes on groundwater recharge (GR), and numerous Global Circulation Model (GCM) and greenhouse gas (GHG) emissions scenarios are currently used for obtaining input data. Studies of future climate change impacts to GR rarely explore assessment and selection approaches (e.g., Vano et al., 2015), and typically do not even rationalize the choice of GCMs selected. With proliferation of models and climate change scenarios, inferences of the new GR projections forces multiple and frequent recalculation of these effects with groundwater models. To constrain the latter step in future developments, we identify only a limited number of projections, while capturing most of the variability inherent among the ensemble of projections. Towards this goal, we use statistics of the cumulative potential groundwater recharge (GR_p), which is defined as the difference between long-term precipitation (P) and actual evapotranspiration (ET) estimates for a future projection period duration of interest (e.g., 40 or 90 years).

This approach starts with developing a set of projections of GR, finding cumulative GR_p for each GCM/GHG scenario that can be coupled with a land surface hydrology model over the projection period, and calculating statistics of the spatial average GR_p dataset in the area of interest. These statistics permit a large reduction in the projections needed by selecting a small subset of representative GR projections that still represent well the range of projected GR_p changes.

Groundwater recharge projections were developed based on GCM-projected changes in the decadal averages of the difference between *P* and *ET* from publically available, downscaled, GCM and land surface hydrology model (Variable Infiltration Capacity—VIC) outputs, under Intergovernmental Panel on Climate Change (IPCC) SRES scenarios of global GHG emissions. This approach is illustrated by the case of the Nebraska Sand Hills (NSH), where sandy soils are not conducive to overland flow. Changes in decadal-averages of GR_p at 1/8° (~12-km) scale were estimated from 16 commonly used spatially downscaled, bias-corrected GCM under three GHG emissions scenarios. Of the 48 GCM/VIC hydroclimate model projections, the GR_p changes were estimated and applied as adjustments to the baseline 2000–2009 GR_p at 1-km scale. The latter were inferred from a previously calibrated groundwater model, with *ET* derived from remote sensing (MODIS) temperature data of 2000–2009, and calibrated GR allowing a match with regional baseflow to streams. After obtaining cumulative (over a period of 40 and 90 years), spatially averaged GR_p from 48 projections, three GR projections (Median, Wet, and Dry) were selected for the Nebraska Sand Hills (NSH).

In the NSH, the 90-year Median projection indicates a spatially averaged GR_p increase of 3 mm/yr (+5%) by the end of the century, relative to the 2000–2009 baseline of 52.6 mm/yr. The Wet projection indicates an average increase of 22 mm/yr (+42%), and the Dry projection yields an average decrease of 15 mm/yr (−29%), relative to the baseline. The projected GR_p estimates are consistent with other large-scale analyses of the region and indicate the possibility for substantial future changes in the NSH hydrologic system. Our estimate resolves variance in interpretations of GR trends between Rosenberg et al. (1999) and Crosbie et al. (2013).

High infiltration rates of the sandy soils reduce overland flow in the NSH and groundwater lag time between precipitation events and actual recharge at the water table, which is within 3–7 years on average in the NSH, even with future potential climate changes—shorter than the decadal time step utilized in the current study. This is an important consideration in groundwater modeling, defined by the hydraulic properties and thickness of the vadose zone (cf., Cook et al., 2003; Rossman et al., 2014). Use of GR projections to understand impacts on groundwater systems elsewhere need to consider the issue of groundwater system response time (Green et al., 2011). For example, response times are becoming considerably shorter during wet conditions with higher GR rates. Another factor affecting the response time is distance between drainages; GR changes may take considerable time (centuries) to affect the entire groundwater system.

Uncertainty in GR rates is generally considered to be caused by both GCMs and GHG emissions scenarios (Crosbie et al., 2011). However, analyses of dynamic feedbacks between changing wetland coverage, streamflows, climate variables, and groundwater flow simulations will certainly be required in future modeling studies. The decision to exclude these processes was based on adequate local information on the geology, climate, and vadose zone flows, which may not be appropriate in other study areas.

This methodology allows for rapid screening of the sensitivity of regional groundwater models to GCM-projected climate changes and assessing the absolute changes in future GR_p and changes relative to a baseline from the recent historical period. Future investigations may require assessment of GR projection temporal variability resulting from individual GCMs at smaller time steps. This is not a problem as available hydroclimate data are typically resolved at the daily to monthly scale.

Finally, it is important to note that wet projections may include decades of drought, while still having the largest total GR over the entire projection period. Therefore, use of commonly accepted climate change scenarios requires a clearly defined assessment of the projection period duration—wet projections may not be the wettest, and dry projections may not be the driest, consistently over such projection period.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2017.09.019.

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